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Design Optimization of Structural Health Monitoring Systems

Eric B. Flynn, PhD

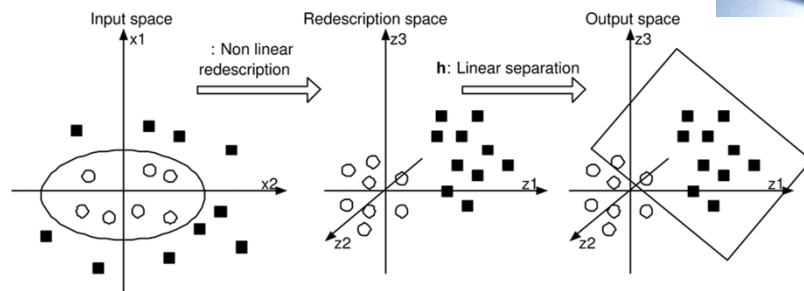
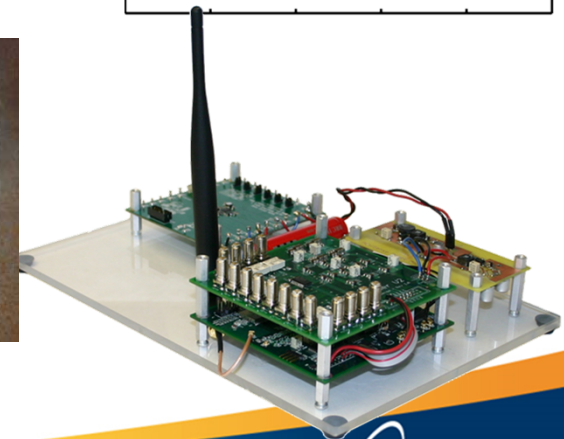
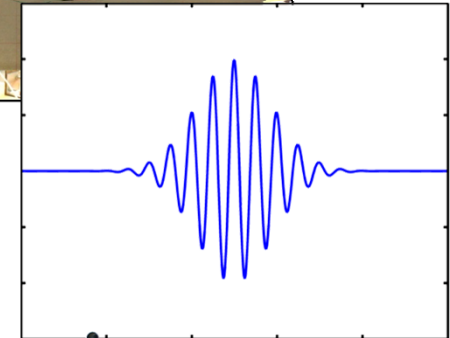
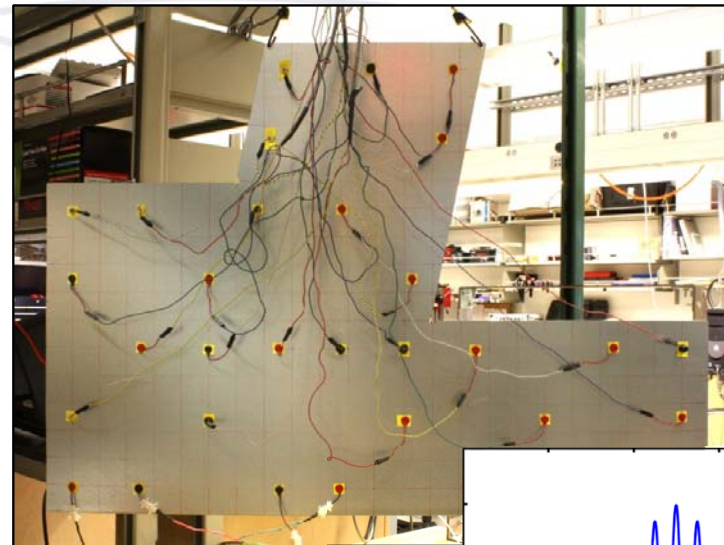
Abstract

Sensor networks drive decisions. Approach: Design networks to minimize the expected total cost (in a statistical sense, i.e. Bayes Risk) associated with making wrong decisions and with installing, maintaining and running the sensor network itself. Search for optimal solutions using Monte-Carlo-Sampling-Adapted Genetic Algorithm. Applications include structural health monitoring and surveillance.

System Design

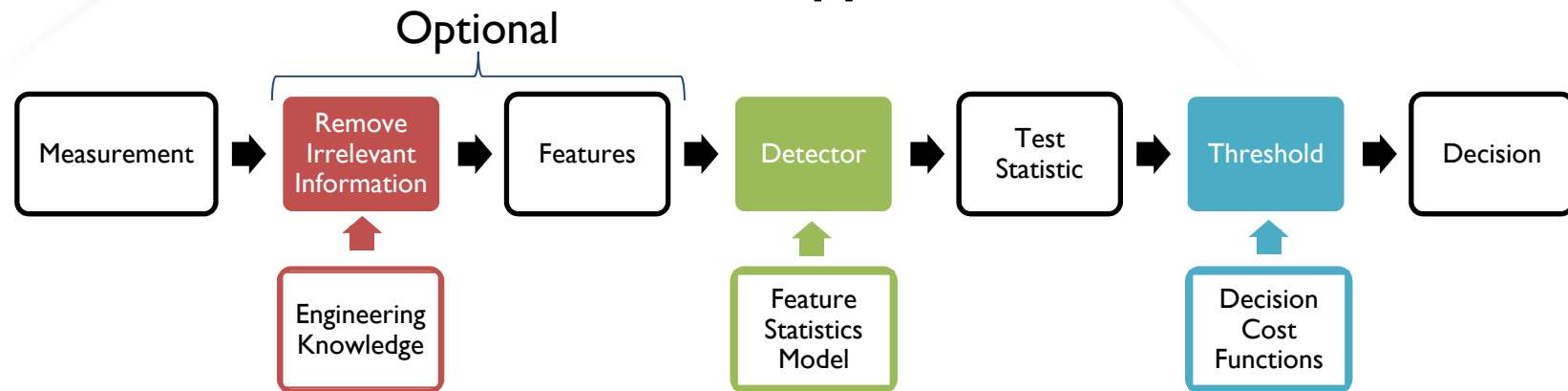
Example design choices

- Detection Algorithm/Classifier
- Sensor Count
- Sensor Placement
- Sensor Orientation
- Sensor Type
- Interrogation Signal
- Duty Cycle

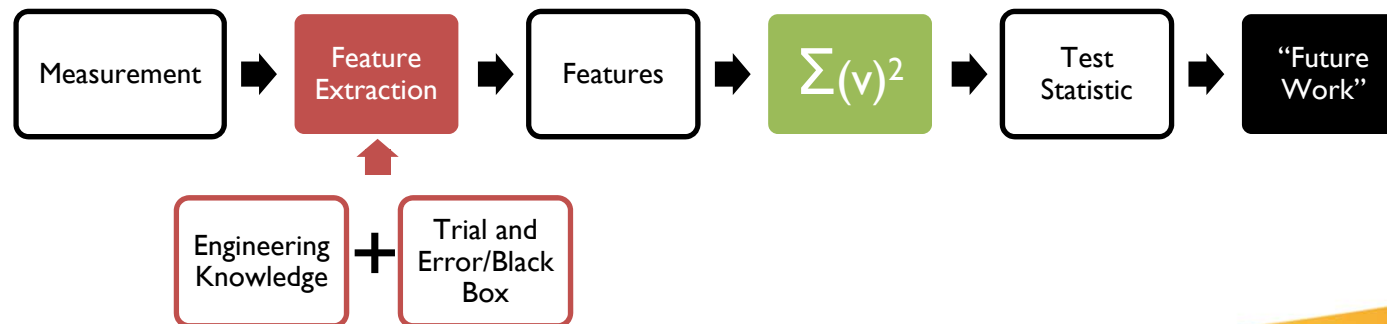


Structural Health Monitoring

LANL Approach



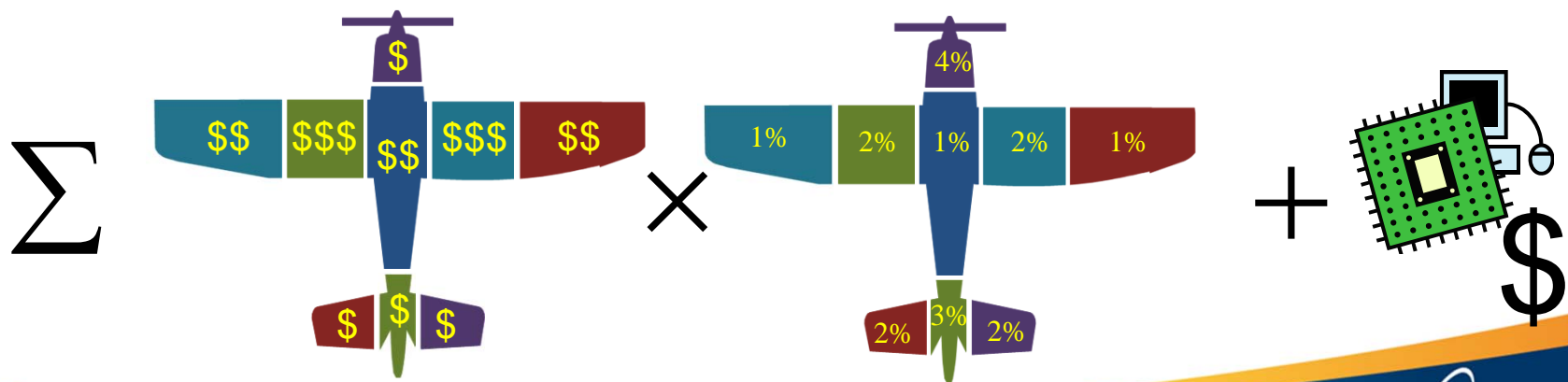
What everyone else does...



Suggested Metric: Bayes Risk

$$E(L) = \sum_{\theta, \hat{\theta}} L_d(\hat{\theta}, \theta) P(\hat{\theta} | \theta, e) P(\theta) + L_e(e)$$

Decision Cost Function
 Particular System Design
 Expected Loss (Bayes Risk)
 Decision State
 True State
 Hardware Cost of the Design



Defining the Problem

- What are the **relevant physical states** and their **probability** of becoming a reality?
- What **actions** is the system intended to direct in response to the physical states?
- What are the **decision costs** of taking each of those response actions?
- What are the **system hardware costs** associated with the surveillance design?

$$E(L) = \sum_{\theta, \hat{\theta}} L_d(\hat{\theta}, \theta) P(\hat{\theta} | \theta, e) P(\theta) + L_e(e)$$

The equation is annotated with colored arrows: a purple arrow points down to L_d and up from $\theta, \hat{\theta}$; a blue arrow points down to $\hat{\theta}$ and up from θ ; a green arrow points down to $P(\hat{\theta} | \theta, e)$ and up from θ ; a red arrow points down to $P(\theta)$ and up from $L_e(e)$; and a light blue arrow points down to $L_e(e)$ and up from e .

Two-part Design Process

Hardware Design

e



Physical State
 $v \sim v(\theta, e)$
Measurements/
Features



Algorithm Design

$\hat{\theta} = \delta(v, e)$

$P(\hat{\theta}|\theta, e)$
Performance Statistics

$$E(L) = \sum_{\theta, \hat{\theta}} L_d(\hat{\theta}, \theta) P(\hat{\theta}|\theta, e) P(\theta) + L_e(e)$$

Detection Algorithm Design

The Bayes optimal detection algorithm:
Make the decision that minimizes expected risk given
measurements/features.

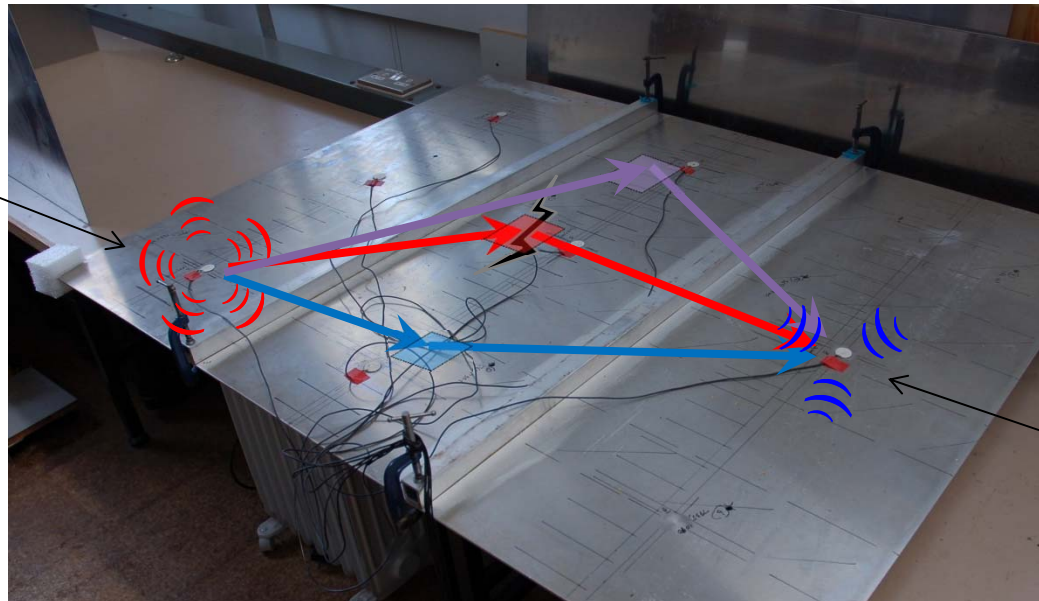
Optimal Decision Likelihood Function
(Feature Statistics) Decision Cost Function

$$\hat{\theta}^* = \delta^*(\mathbf{v}, e) = \arg \min_{\hat{\theta}} \sum_{\theta} \underbrace{p(\mathbf{v} | \theta, e)}_{\text{Likelihood Function (Feature Statistics)}} \underbrace{L_d(\hat{\theta}, \theta)}_{\text{Decision Cost Function}} P(\theta)$$

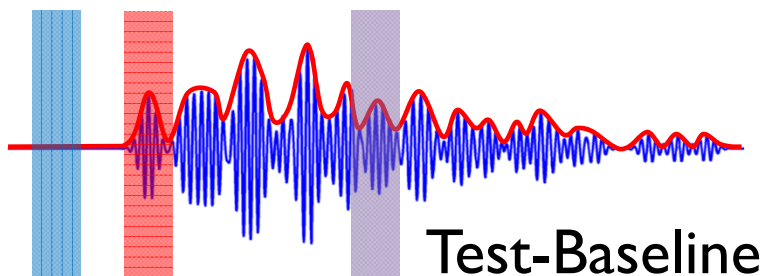
Sum over potential physical states

Embedded Ultrasonic Inspection

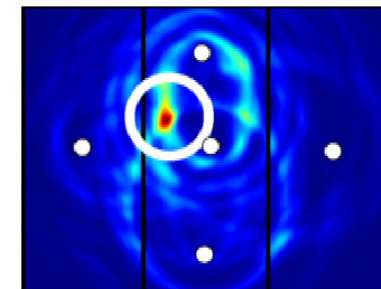
Actuator



Sensor



Delay-and-sum

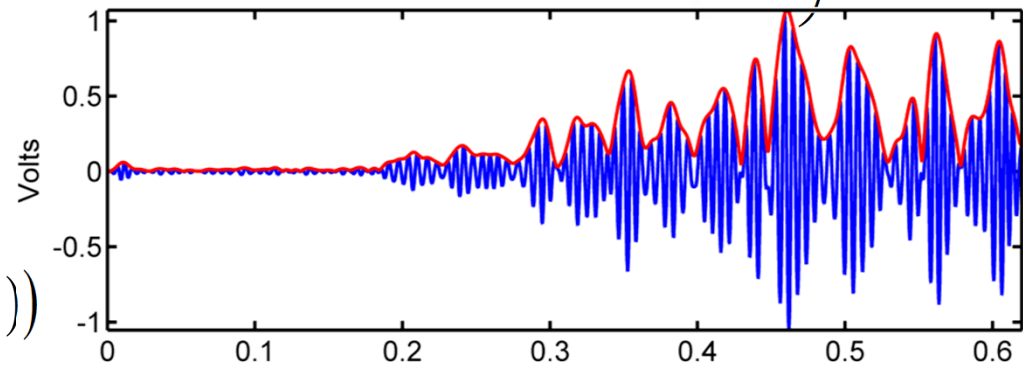


Maximum *a posteriori* probability estimate

$$L(\theta_{xy}) = \sum_{\text{Pairs}} \left(\sum_{\text{Time Samples}} \log \left(p(v_1 | \theta_{xy}) \right) + \log \left(p(v_2 | \theta_{xy}) \right) \right)$$

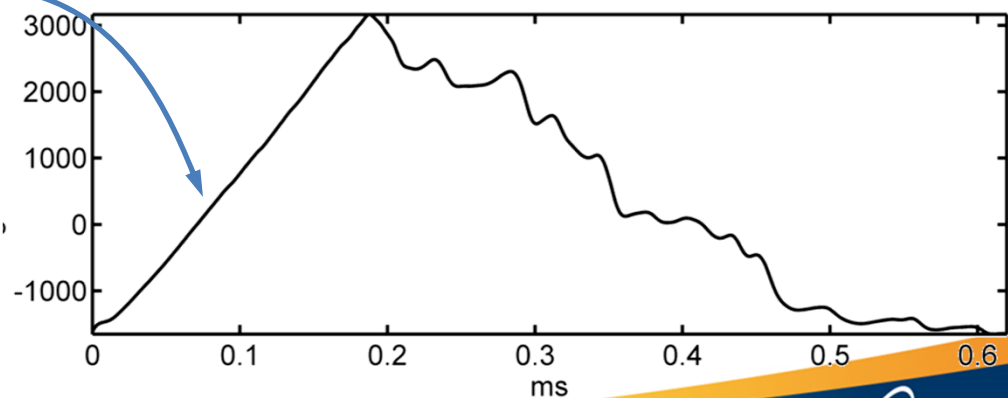
Time of Flight

$$L(\mathbf{x}) = \sum_{m=1}^M w_m [\eta_m(\mathbf{x})] + \log(p(\mathbf{x}))$$

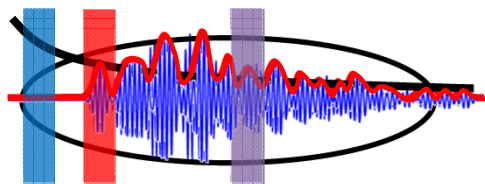


$$w_m[\eta] = -\eta \log \left(\sum_{n=1}^{\eta} v_m^2[n] \right)$$

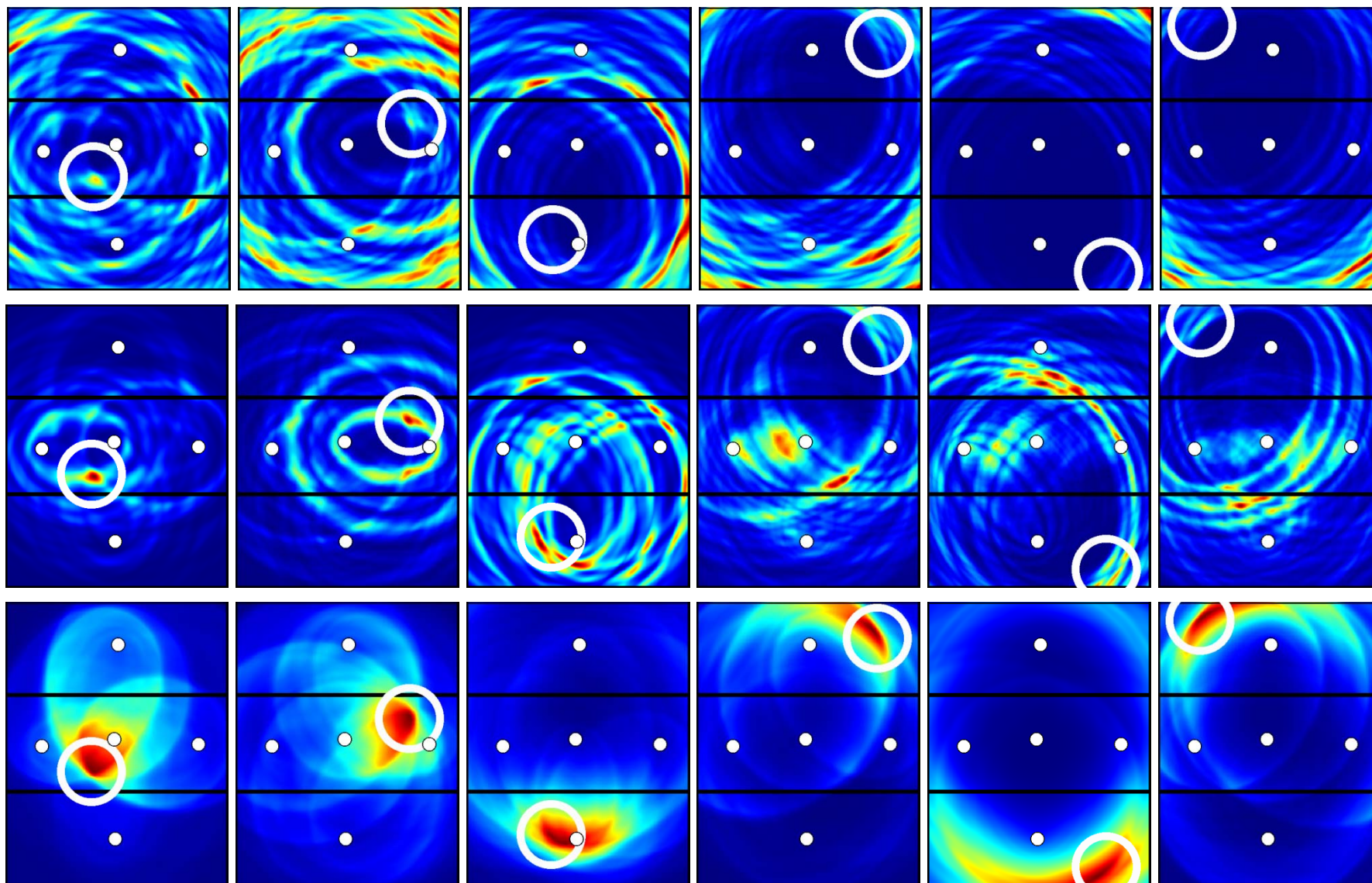
$$- (N - \eta) \log \left(\sum_{n=\eta+1}^N v_m^2[n] \right) + \log(\eta!(N - \eta)!)$$



Comparison

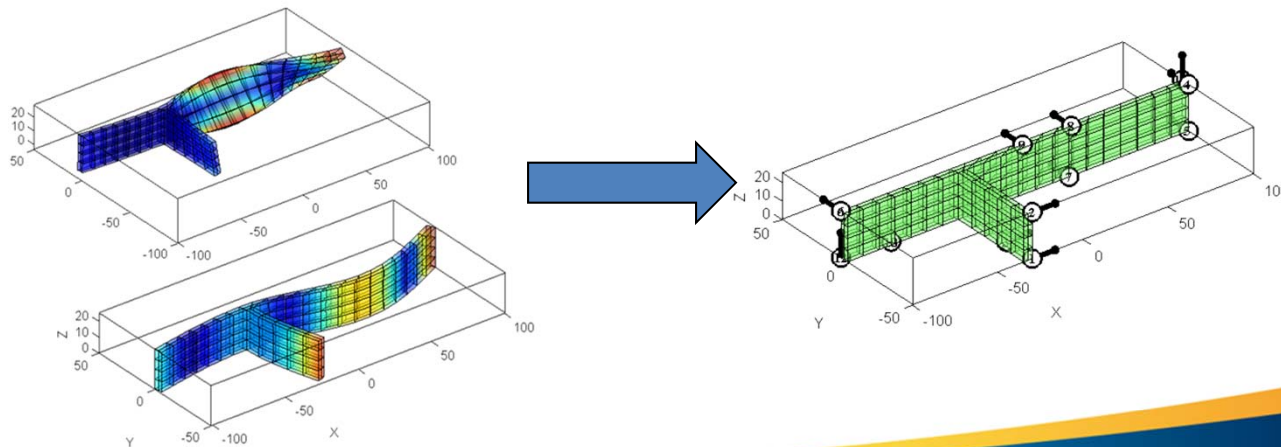


Envelope and Delay
Summing
Statistical Modeling
and Sum



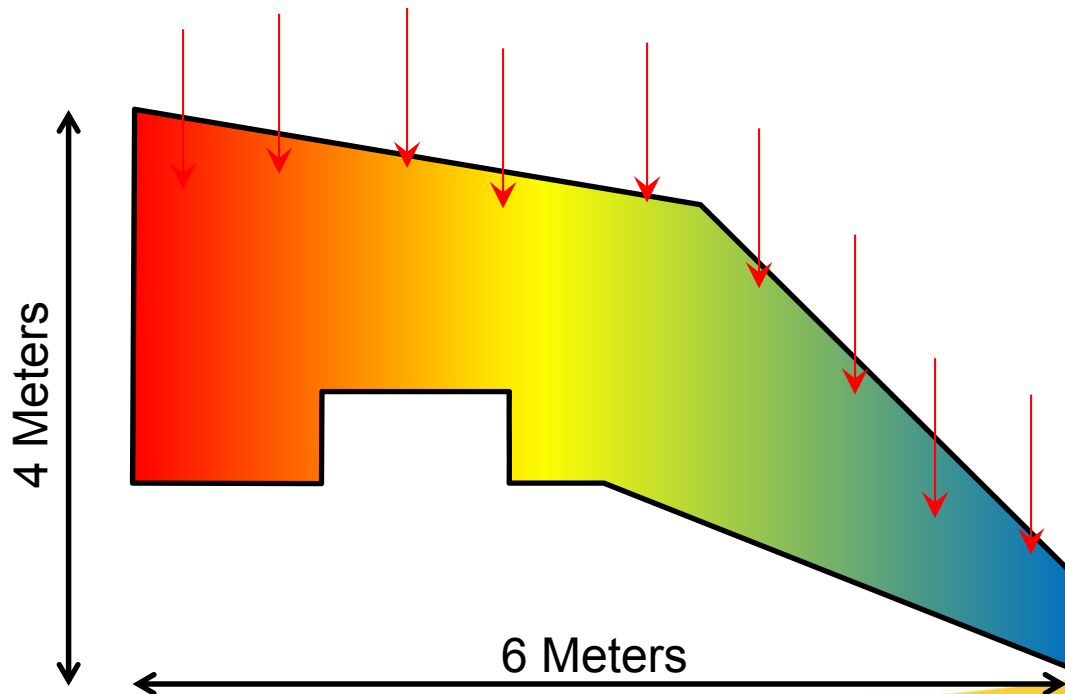
Hardware Design

- Define the monitoring problem
- Establish feature measurement process
- Design detection algorithm based on measurement statistics **parameterized to hardware design variables**
- Calculate system statistics and performance (Bayes Risk)
- Search hardware design space for optimum

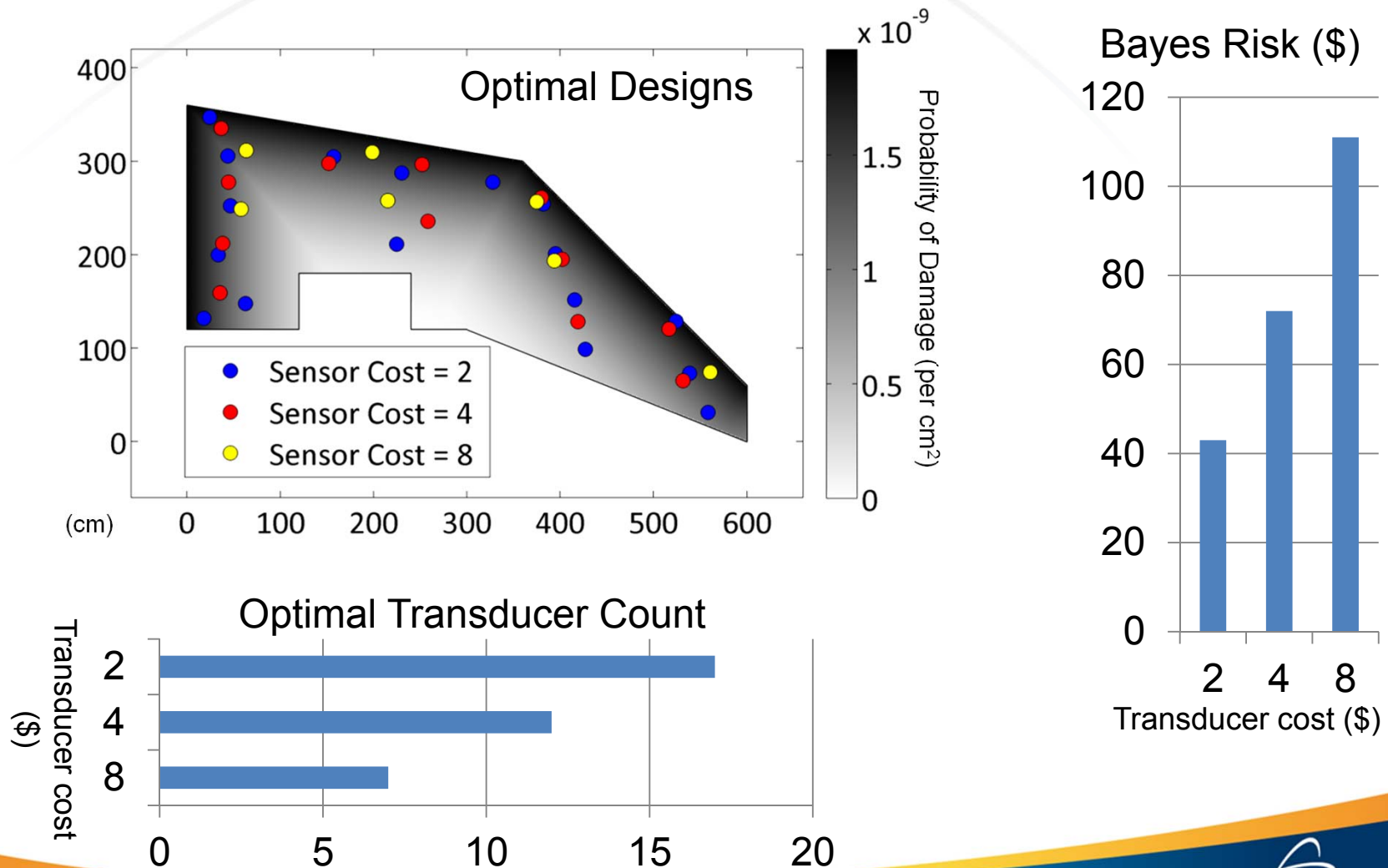


Hardware Design Example

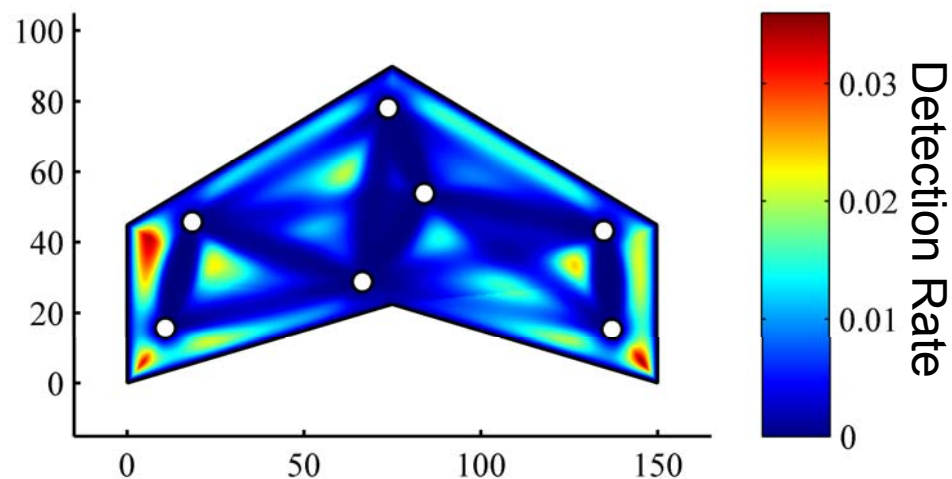
- Monitoring of aerospace component skin
- Structure undergoes bending and torsional fatigue loading and is subject impacts on its leading edges
- Optimize the number and the placement of transducers



Optimization Results

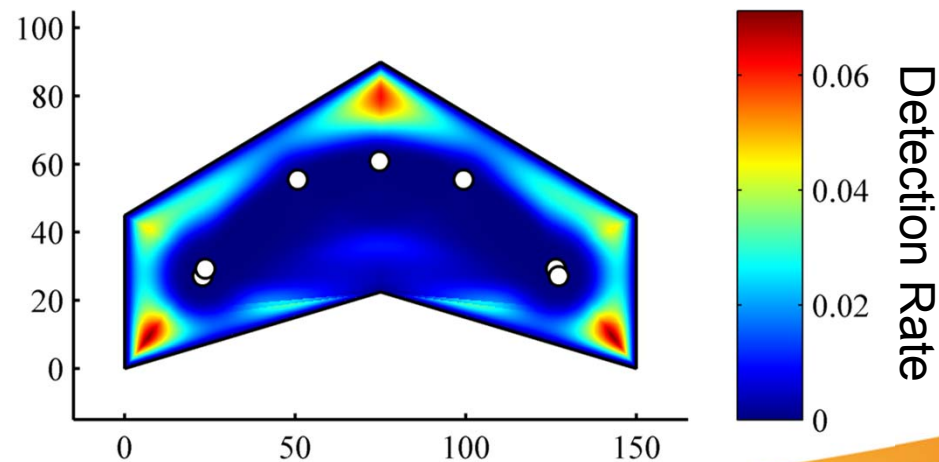


Sensor Failure



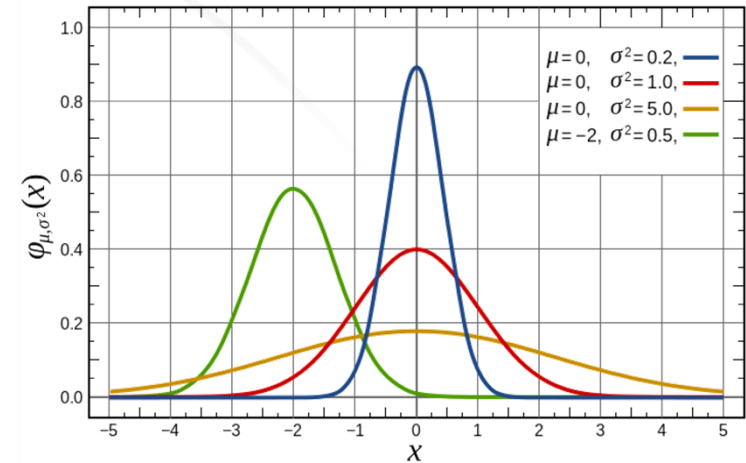
No Sensor Failure

10% Chance of Sensor Failure



The Hard Truth

The world doesn't look like this:



Which means:

- Optimal detectors are intractable
- Detector statistics are intractable
- Detector performance is intractable
- Sensor network performance is intractable

Brute Force

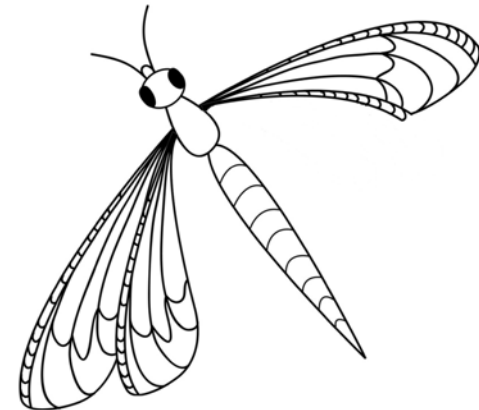
Monte Carlo your way to a performance estimate

- Generate random samples
- **Measure**
- **Detect / Score**
- Threshold
- Estimate the Bayes Risk

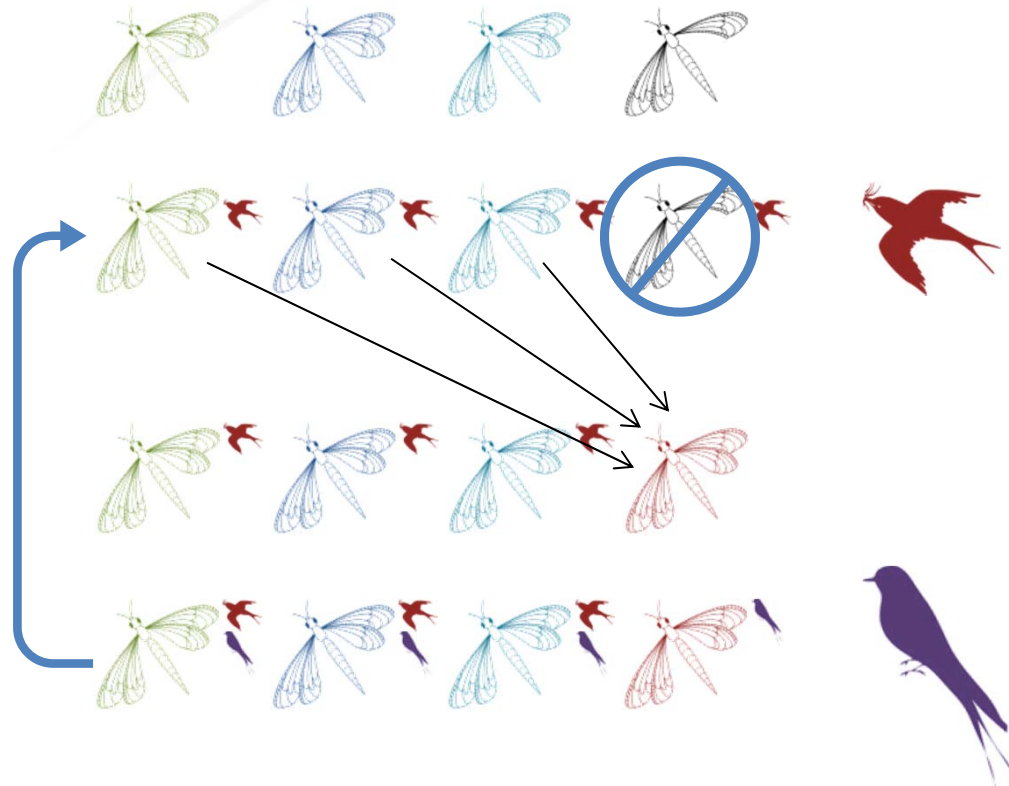
Problem: Takes a long time!

Solution: Sampling Adapted Search

- It doesn't take a "life-time" worth of Monte Carlo trials to determine that some designs just won't cut it



A Smarter Genetic Algorithm



Generate population

Generate small random sample, subject, and evaluate performance

Destroy the worst performers

Survivors remember past samples

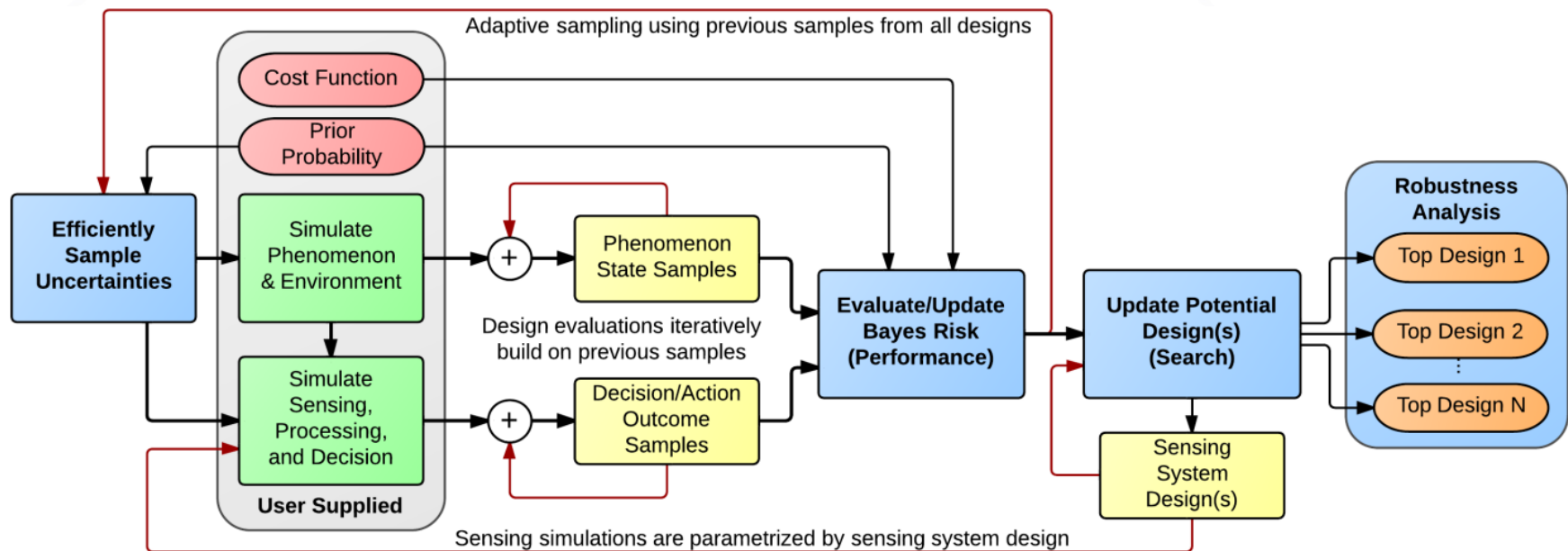
Crossover and mutate the survivors to repopulate

Generate new random sample and subject

Evaluate performance based on all previous samples

Respect your elders: The best design is the oldest design, not necessarily the best performer.

Plug-and-play Optimization



Surveillance Problem

Chemical, Biological,
Radiological, Visual

Source

Known:

Occurs only at ground level
Radial dependency ($1/r_2$)

Unknown:

Location
Initial Intensity

Cost Function

Event Occurs: \$1.0 B
Evacuation: \$10.0 K

Prior Probability

1.0% over 10 years

Sensor Placement

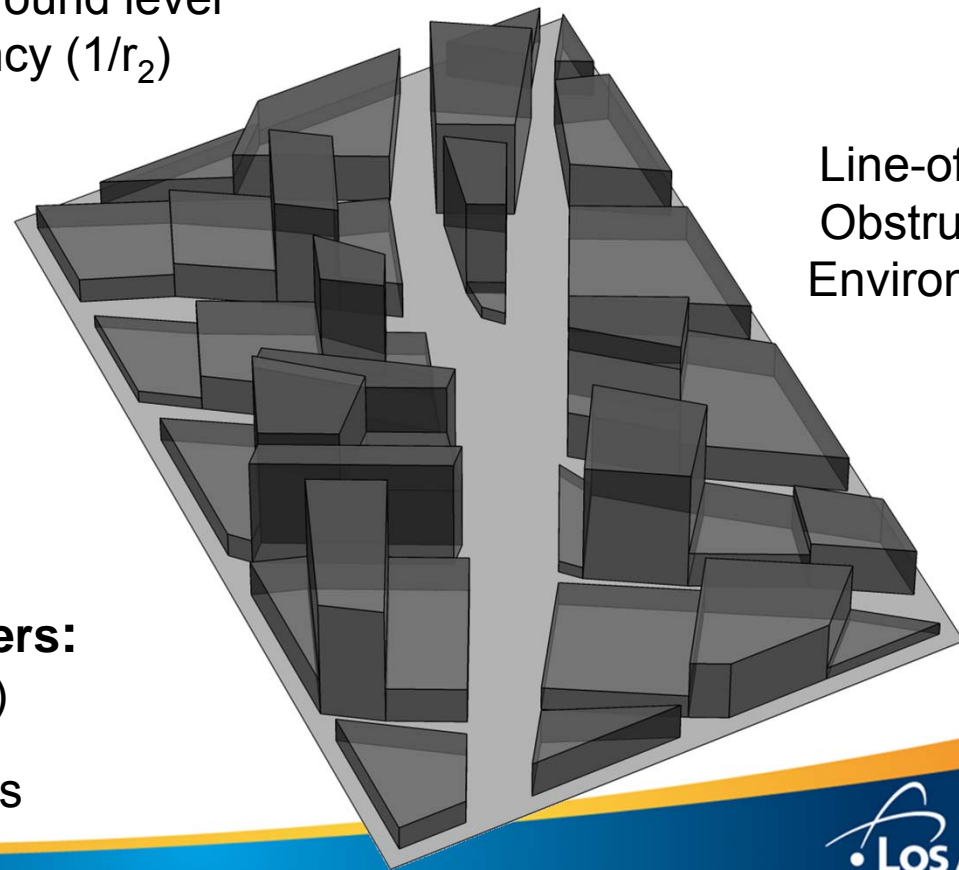
Measurement:

Intensity

Design Parameters:

Position (X, Y, Z)

Fixed: 10 Sensors



Line-of-Site
Obstructing
Environment

Sensor



Missed Agent Detected Agent

